Determining the Composition and Collectibility of Child Support Arrearages

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Semi-Annual Performance Report of the Research Project
New Approaches to Collecting Child Support Arrearages:
Determining the Composition and Collectibility of Arrearages

Second Report
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Second Performance Report

This semi-annual progress report covers project activities for the period April – September 2000. During this period project work continued on schedule. This report includes a brief statement of the project research plan, a summary of project activities for the period, and some preliminary data analysis. The financial status report will be sent separately.

Summary of Project Plan

This is a study to determine the patterns of debt growth in Washington State child support cases. Our goals are to understand the processes and components of child support that lead to large debts; document the mitigating effects of interventions on collectibility; determine the impact of law and policies on debt growth; and recommend changes that will lead to lower arrearages.

To accomplish these goals, our objectives in this project are as follows:

- To quantify the rate of arrearage growth;
- To develop a model to predict debt growth outcomes and collectibility;
- To quantify the interaction of parents' usage of public assistance programs, participation in work activity programs, and payment of child support to determine the impact of interventions on debt collectibility;
- To document which field interventions are most effective in working older cases with high arrearages;
- To develop a model to chart points of return per effort (cost effectiveness breakpoints);
- To document the effect of Washington State's statutes, codes, and policies on the life cycle of the child support debt process;
- To prepare recommendations for changes necessary to optimize collectibility of debts, write off bad debt, and minimize future arrearage building;
- To evaluate the effectiveness of DCS programs in light of the federal incentive measure on arrears.

There are several parts to this study. The main part of the project is based on construction and analysis of a large database containing information on child support cases, noncustodial parents, other parties to the cases, and other public program usage. Longitudinal data analysis and neural network analysis will be used to develop a model for predicting debt outcomes.

The center of the study is the cohort of noncustodial parents (241,731 persons) listed on the universe of open child support cases present on SEMS (the DCS case management computer system) in third quarter 1995. Our longitudinal database enables us to track these individuals for 15 quarters, from fourth quarter 1993 to second quarter 1997. With this cohort we can look back seven quarters and forward seven quarters. This period was chosen because it is a relatively stable period before welfare reform was implemented. The model can then be applied to other time frames.

Our database also contains information on the other parties to those cases, i.e., the custodial parents and children. Consequently, we can link individuals to multiple cases.

The work of constructing the database, completing data share agreements, and conducting the cross-matches was completed in the first six months of the project, as we reported in our first performance report. In addition, Carl Formoso undertook preliminary work with neural network modeling.[1]

Through cross-matches with other administrative databases, we can measure networks of program usage, such as public assistance, mental health or alcohol/drug treatment, or vocational rehabilitation. We will develop an assistance and program usage profile.

We will analyze this data to determine the distribution of arrears patterns (increasing, decreasing, remained same, up and down). The techniques of logistic and neural network modeling and survival analysis will be used to develop the model for predicting debt outcomes.

The second part of the study is a case assessment based upon stratified samples representing debt patterns identified by the model. The sample cases are being examined by an experienced support enforcement officer (SEO). The SEO reviews the case to determine how the obligation was set for the original order, the history of modifications, the noncustodial parent's income history, number of child support cases, payment record, and significant DCS enforcement actions and other interventions. The SEO also checks for evidence that DCS was aware of such factors as disability, public assistance usage, corrections record, and other barriers to collection, and evaluates DCS response in such instances.

This two-tiered analysis of debt patterns on child support cases will allow us to quantify the rate of arrearage growth, reliably predict debt growth outcomes and collectibility, determine cost breakpoints, and explain why the patterns occur. We want to document not only what is happening, but also why it is happening.

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[1] *Determining the Composition and Collectibility of Child Support Arrearages*, First Performance Report, MAPS Unit, Division of Child Support, May 2000, especially pp.3, 6-8.

Two other parts of the study were substantially completed during the first six months of the project. We examined the contribution of various programs, including federally mandated ones, to increasing DCS collections on child support arrears. We examined DCS field office pilot projects and other local initiatives to assess their role in reducing child support debt. Of particular interest were field office projects implemented as part of WorkFirst (Washington's welfare-to-work program). We also investigated projects specifically aimed at hard-to-work cases with large debts. Our first progress report discussed DCS initiatives in some detail.[2]

Another part of the study is to review Washington statutes and policies that govern how child support debt is handled over the lifetime of the case. Washington law contains provisions for charging off child support debts deemed uncollectible or reducing such debts for hardship when the debts are owed to the state (i.e., DSHS). Such reviews are conducted on a case-by-case basis as requested.

Our first progress report discussed the impact of certain statutes and policies, such as the statute of limitations on child support debt, requiring the noncustodial parent to sign a waiver of the statute in return for lowering monthly payment amounts, and the use of imputed income in setting order amounts. The report reviewed current DCS initiatives aimed at speeding up and simplifying the process of correcting orders. It discussed initiatives to streamline the debt reduction process as well.

Finally, on the basis of our findings, we will recommend ways to manage debt on old cases and to avoid practices that appear to contribute most to arrearage growth. If it appears that certain statutes and practices are outdated and contribute to rapid arrearage growth, project findings may recommend changing them. We hope to suggest expedited remedies for review of cases determined to be uncollectible. We will suggest strategies and program changes that appear effective in responding to new federal requirements.

For more detail on the project's schedule of work, please see the Project Time Line Chart attached as Appendix A to Part 1.

[2] *First Performance Report,* May 2000, especially pp. 18-38.

Part 1

Project Work during the Past Six Months

Launching the case assessment part of the project was a major focus of work. The assessment is based on a stratified sample of noncustodial parents representing debt patterns identified by the model. The analysis will of course draw upon data from recent flatfile extracts as well as information in the project's central database. But the focus here is on intensive review of the cases to capture information from case comments and other sources not preserved in flatfiles. For example, we want to know the basis used for setting the original child support amount (actual income, imputed median net, etc.). We want to know what locate and collection tools were used. When noncustodial parents have multiple cases, we want to know how much overlap there is among those cases (in children, custodial parents, and orders).

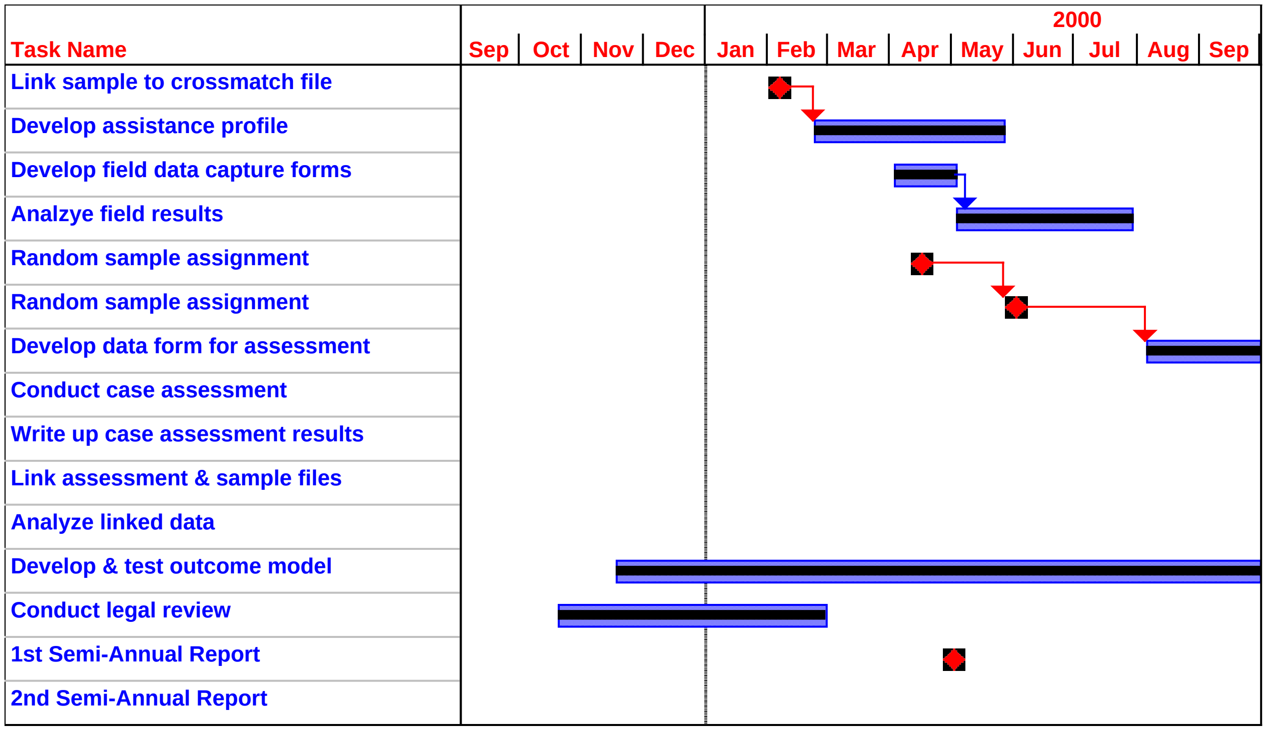
We developed a questionnaire to capture this information. A project staff member reviews the sample cases on SEMS and codes information directly into a Microsoft Access file. A copy of the questionnaire is attached as Appendix B to Part 1.

We selected Jeannie Anthony as the Program Analyst to do the intensive case review and coding. Jeannie is an experienced Support Enforcement Officer (SEO 2) from the Tacoma field office. In addition to carrying a regular case load, Jeannie wrote a helpful manual for SEOs on using ACES, the computer system used by the IV-A program in Washington to track public assistance clients. Prior to working for DCS, Jeannie worked for three years as a Financial Services Specialist in a CSO, so she has considerable knowledge of public assistance programs and agility in moving between two computer systems: SEMS and ACES. Her resume is attached as Appendix C to Part 1.

Jeannie participated in developing the case assessment questionnaire. In addition to drafting some of the questions, she helped to translate the written instrument into Access format. Access has proved to be a flexible program, allowing her to continue to experiment with the sequence of questions to enhance efficiency. Coding is now well underway.

Appendix A

Project Time Line Chart


Task Name
2000
Sep
Oct
Nov
Dec
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Link sample to crossmatch file
Develop assistance profile
Develop field data capture forms
Analzye field results
Random sample assignment
Random sample assignment
Develop data form for assessment
Conduct case assessment
Write up case assessment results
Link assessment & sample files
Analyze linked data
Develop & test outcome model
Conduct legal review
1st Semi-Annual Report
2nd Semi-Annual Report

Appendix B

Case Assessment Questions

This data capture instrument was designed to supplement information available through flatfile extracts. Answering the questions requires experience as a support enforcement officer. Most of the answers must be retrieved by reading case comment screens. The project's program analyst codes the answers directly into a Microsoft Access database rather than on a paper copy.

Division of Child Support
Arrears Project

Case Assessment

Date Coded: __-__-____

Noncustodial Parent and DCS Collection Work

NCP identifiers for matching

1. Social Security Number ___-__-____

2. BI number _________

Payment/Debt Patterns according to Model

3. Quadrant 1993-97 *[check one]*
   __ Steadily increasing arrears
   __ Steadily decreasing arrears
   __ Up and down
   __ No change

4. __ Did the pattern change after this period? *[check mark means yes]*

Multiple cases
[Exclude non-IV-D cases. Also exclude the following IV-D cases: Paternity Establishment Only; NCP excluded as father; cases closed at SEO discretion within 90 days of opening.]

5. On how many IV-D cases is this individual listed as NCP? ____

6. How many <u>different</u> children are linked to IV-D cases where this individual is NCP? ____

7. How many <u>different</u> custodial parents are linked to IV-D cases where this individual is NCP? ____

8. On how many IV-D cases is this individual listed as CP? ____

9. How many <u>additional</u> children are linked to this individual as CP? _______

10. Maximum sum of monthly order amounts (SMOA) for this NCP $_________

11. Year when this SMOA began _______

12. Year this SMOA ended if different ______

13. Number of open cases at time of maximum SMOA ______

Collection Barriers

14. Did the NCP receive public assistance or SSI while DCS was working the case(s)? [*Check all that apply*]
__ AFDC/TANF
__ GA-U, GA-X
__ Food stamps only
__ SSI

15. Corrections, arrests, etc. *(Check all that apply)*
__ NCP has a Department of Corrections (DOC) number
__ NCP incarcerated while DCS was working the case(s)
__ Case comments *[begin 1993*] refer to arrests, jail, prison, etc.

16. Is there evidence that the NCP had substance abuse problems while DCS was working the case? *(Check all that apply)*
__ NCP on GA-W grant.
__ Case comments *[begin 1993]*.

17. __ Level A Good Cause?

Interstate

18. If there are interstate issues:
__ IJ (Washington was Initiating)
__ RJ (Washington was Responding)
__ Neither, but the NCP was in another state
__ Intermittent

If IJ:

19. Date initiated __-__-____

20. Date received any money. __-__-____

Locate and Collection Efforts/Remedies

21. Which locate tools are documented for this NCP? *[Begin case comment review in 1993 and check all that apply]*
    __ ES/UC/IT IS
    __ DOR/MLS
    __ DOL
    __ DOL/NWEP
    __ SCOMIS/DISCIS
    __ S.O. Locate
    __ WICP/CSENet
    __ Credit Bureau
    __ DOC/FORS
    __ 18-013
    __ 18-002
    __ Telephone calls
    __ Other ___________________

22. Collection tools *[Check all that apply]*
    __ PDN/OWD
    __ Contempt referral
    __ Seizure (NWEP seizure process started or vehicle/vessel lien placed)
    __ County lien filed
    __ IRS certification
    __ Letter to NCP
    __ Telephone calls
    __ URESA/UIFSA
    __ License suspension (DSHS 09-851 sent)
    __ EFT
    __ Other __________________

23. ___ Did DCS agree to lower monthly payments on arrears? *[Check mark means yes]*.

24. Were some payments received from IRS offsets? *[Check one]*
    __ All
    __ Some
    __ None

25. Were some payments received from the social safety net? *[Check all that apply]*
    __ SSA
    __ Veterans
    __ L&I
    __ Unemployment compensation
    __ Disability dependent benefits credited

Case Coding

[Repeat Case Coding section of questions for each case.]

26. Case (IV-D) number ______________

27. Case type when first opened: ___

28. Case type on coding date: ____

29. Subro type on coding date: ____

30. __ Has this case ever been closed and reopened? *(Check mark means yes]*

31. __ Order established?: *[Check mark means yes]*
    [If no, skip to question 77 on case closure.]

32. If Washington was Responding Interstate (RJ), did other state set the MOA?
    __ Yes
    __ No

33. If RJ, total arrears when DCS received the case: $___________

[If other state set MOA, skip rest of case assessment to question 71.]

34. If Initiating Interstate (IJ), was the MOA set by other state?
    __ Yes
    __ No

Original order(s)

35. Same as order on D# __________.
[If same order as on another case already coded, enter that case number and skip to question 64.]

36. Number of original orders for case: ___

37. If court-ordered judgments:

    a. Child support arrears owed to Custodial Parent: $____________

    b. Child support arrears owed to DSHS: $____________

    c. Child support arrears owed to another state: $__________.

    d. Paternity/medical subro (not IV-D debt): $___________

38. Administrative arrears at establishment: $___________

a. Child support arrears owed to Custodial Parent: $____________

b. Child support arrears owed to DSHS: $____________

c. Arrears owed to another state: $____________

39. __ Was original order reviewed (did coder review copy of order)? *[check means yes]*

40. Basis for setting the original order amount: *[check one]*
    __ Actual income
    __ % of net
    __ Imputed from ES or employer
    __ Imputed median net income
    __ Imputed need standard
    __ Imputed grant standard
    __ Imputed minimum wage
    __ Other state
    __ Other _________________
    __ Can't tell

41. __ Is this a paternity order?: *[Check mark means yes]*

42. If yes, blood test done? *[check one*]
    __ Yes
    __ No
    __ Can't tell

43. Default paternity order? *[check one*]
    __ Yes
    __ No
    __ Can't tell

44. __ Was the case referred out of state for paternity establishment? [*check mark means yes]*

45. If additional original order, basis for setting amount: *[check one]*
    __ Actual income
    __ % of net
    __ Imputed from ES or employer
    __ Imputed median net income
    __ Imputed need standard
    __ Imputed grant standard
    __ Imputed minimum wage
    __ Other state
    __ Other ______________
    __ Can't tell

46. __ Is this a paternity order?: *[Check mark means yes]*

47. If yes, blood test done? *[check one]*
    __ Yes
    __ No
    __ Can't tell

48. Default paternity order? *[check one]*
    __ Yes
    __ No
    __ Can't tell

49. __ Was the case referred out of state for paternity establishment? *[Check mark means yes]*

50. If third original order, basis for setting amount: *[check one]*
    __ Actual income
    __ % of net
    __ Imputed from ES or employer
    __ Imputed median net income
    __ Imputed need standard
    __ Imputed grant standard
    __ Imputed minimum wage
    __ Other state
    __ Other ___________
    __ Can't tell

51. __ Is this a paternity order?:*[check mark means yes]*

52. If yes, blood test done? [*check one]*
    __ Yes
    __ No
    __ Can't tell

53. Default paternity order? *[check one]*
    __ Yes
    __ No
    __ Can't tell

54. __ Was the case referred out of state for paternity establishment? *[check mark means yes]*

55. If fourth original order, basis for setting amount: [*check one]*
  - __ Actual income
  - __ % of net
  - __ Imputed from ES or employer
  - __ Imputed median net income
  - __ Imputed need standard
  - __ Imputed grant standard

  - __ Imputed minimum wage
  - __ Other state
  - __ Other _______________
  - __ Can't tell

56. __ Is this a paternity order?: *[check mark means yes*]

57. If yes, blood test done? *[check one*]
  - __ Yes
  - __ No
  - __ Can't tell

58. Default paternity order?
  - __ Yes
  - __ No
  - __ Can't tell

59. __ Was the case referred out of state for paternity establishment?
[check mark means yes]

60. At the time an order was entered: *[Check all that apply]*
  - __ Was the NCP on public assistance?
  - __ Was the NCP on SSI or other disability-related program?
  - __ Was the NCP incarcerated?
  - __ Did DCS know about this at time of case set-up?

Modifications

61. How many times was this case modified? ____

62. Who requested the first modification:
  - __ Custodial Parent
  - __ Noncustodial Parent
  - __ State
  - __ Can't tell

63. Direction of first modification?
  - __ Downward
  - __ Upward

Statute of Limitations Issues on Case

64. __ Was debt calc done for SOL? [*check mark means yes*]

65. Amount lost from SOL. $_________

66. __ Did the NCP sign a waiver of the SOL? *[check mark means yes]*

67. __ No SOL applies because of administrative order's date.
[Check mark means no SOL applies.]

68. __ No loss to SOL because of other state's law.
[*Check mark means no loss to SOL]*

Debt loss and adjustments

69. If DCS adjusted some IV-D debt on the case (other than for SOL], *check all of the following reasons and circumstances that apply:*
__ Death of a party to case
__ Vacated order
__ NCP and CP reconciled
__ Legislative change or judicial decision
__ CP gave additional credit
__ Conference Board
__ Hardship
__ Lump sum settlement
__ Error or legal defect makes full collection unlikely
__ Low collection potential considering costs to agency

70. Amount reduced under question 69 $___________

71. __ Has current support (CFS) ended? *[check mark means yes]*

72. If so, date ended: __-__-____.

If case is closed
[Answer only if case is closed at time of coding]

73. Last closure date. __-__-____.

74. Last closure code: ____..

75. Case comment (SEO's) reason for closing case. ______________________.

76. Total paid to Custodial Parent: $___________

77. Total paid to DSHS: $__________.

78. DSHS arrears remaining: $_________.

Appendix C

New Project Staff

Jean Anthony

Education and Qualifications

Bachelor of Arts, Sociology/Philosophy, May 1994
Gonzaga University, Spokane, WA

Two years, eight months experience as a Support Enforcement Officer completing all duties therein including order establishment.

Experience

Created a guide for applying the Whole Family Method—This project involved analyzing the existing material, the WSCSS, and consulting with a Claims Officer. I created a guide to help standardize the way deviations are applied in my unit during order establishment and modification. This guide is now used in my unit and is being examined office wide.

Created ACES resource manual for the office—This project involved analyzing how ACES is used and what information would be pertinent to the case managing SEO. This information was formed into a document that is used office wide.

Responsible for training individual SEO's to use ACES—This involved finding the necessary data in ACES to obtain information for case management and establishment.

Completed basic and advanced facilitator training—I learned the skills on how to analyze a situation quickly and determine the best way to facilitate progress.

Completed *Writing Policy and Procedure* training.

Technical Skills

Computer Software: Microsoft's Word, Excel, Power Point, and Access
Computer Programs: SEMS, ACES

Employment History

October 97 through present Tacoma DCS	Support Enforcement Officer
September 94 to October 97 Kent CSO	Financial Service Specialist

Part 2

Progress On Modeling and Predicting Arrearage Behavior

Carl Formoso

In this period we:

1) Obtained and linked data from four sources:

    a) Child support enforcement (CSE) records from DCS data file extracts,

    b) Eligibility records for use of public assistance from the Office of Financial Management (OFM),

    c) Earnings records for non-custodial parents from the Employment Security Department (ESD), and

    d) Records of public service use by non-custodial parents covering 159 separate programs across five Divisions within the Department of Social and Health Services (DSHS) from the Needs Assessment Database (NADB).

2) Formulated a methodology for evaluation of arrearage predictions and modeling.

3) Made progress in understanding NADB data and its utility in modeling arrearage behavior.

4) Began the process of variable selection and model optimization.

Data

Data on monthly use of public assistance from October, 1993 through June, 1997 was obtained for the non-custodial parent cohort and for associated custodial parents. We have direct computer access to these records.

Data on quarterly earnings from 4th quarter 1993 (CY) through 2nd quarter 1997 were obtained for the non-custodial parent cohort. While we have a data sharing agreement in place, obtaining this data required negotiations with ESD staff for a special run.

We completed data share agreements with five DSHS Divisions and obtained cross-match data on the specific program use within those five Divisions for individuals in the non-custodial parent cohort.

Methodology: Prediction and Information Content

The non-custodial parent (NCP) cohort is selected as all non-custodial parents (N=241,731) in DCS records in 3rd quarter of CY95 (95Q3). In building a prediction model we use the previous 7 quarters and 95Q3 as the ‘observation’ period, and the following 7 quarters as the ‘outcome’ or ‘evaluation’ period. The general approach is to use data from the observation period to predict arrearage behavior in the outcome period. Mostly we have worked with a four category outcome model: based on the arrearage debt in 95Q3, in the outcome period debt can increase (UP), decrease (DOWN), remain the same (SAME), or the data could be missing (MISS) in the outcome quarter.

We use a random sample of 5,000 NCPs (~2% of the cohort, we use the same sample throughout, unless otherwise noted) to develop a neural network simulation. The input to the network are data elements from the observation period, and the parameters of the network are adjusted to obtain the best match with the known outcomes for these individuals. This is referred to as “training the network.” The trained network is then tested by making predictions for each individual in the entire cohort. Predictions are evaluated by comparing with known outcomes.

In evaluating predictions, simply measuring the number of correct predictions is not adequate because it is easier to correctly predict outcomes which are more likely. Using an information theory approach, information content is estimated by the number of binary (yes/no) questions needed to obtain the result. In our arrearage prediction model, considering four possible outcomes, we would need two binary questions for each individual. In the language of information theory one binary question is one 'bit' of information; doing a complete prediction of outcomes would require about 2*241,731 = 483,462 bits of information. But this approach overestimates information when outcomes are not equally likely. The more general relationship (1) below allows an accurate calculation of information content.

$$\mathbf{I} = -\,\mathbf{N}\sum \boldsymbol{P_i} \log_2 \boldsymbol{P_i} \qquad (1)\quad ,$$

where **I** is the information content, **N** is the number of individuals, and $\boldsymbol{P_i}$ is the probability of the *i*th outcome. Estimating $\boldsymbol{P_i}$ as the fractional frequency of occurrence of each outcome, $\boldsymbol{f_i}$, and substituting the number of individuals with each outcome, $\mathbf{N}_i = \mathbf{N} * \boldsymbol{f_i}$, we have:

$$\mathbf{I} = -\sum \mathbf{N}_i \log_2 \boldsymbol{f_i} \qquad (2)$$

Information content is maximized when all outcomes are equally likely and is then equal to the information content estimated by the number of binary questions. We can consider $-\log_2 f_I$ as the bits of information per individual for each outcome. This quantitatively adjusts for the difficulty of correct prediction. We can thus determine exactly the minimum amount of information required to completely predict arrearage outcomes using several possible outcome models. Using actual outcomes in the seventh quarter after 95Q3, a model with two outcome categories would require 234,700 bits of information (Table 1), four categories would require 456,800 bits (Table 2), and six categories would require 610,600 bits (Table 3).

Table 1: Information Required for Predicting Two Outcome Model

	# of Indiv	bits per indiv	Info
UP	96,744	1.321158	127,814
NOT UP	144,987	0.737479	106,925
TOTAL	241,731		234,739

Table 2: Information Required for Predicting Four Outcome Model

	# of Indiv	bits per indiv	Info
MISS	41,851	2.530068	105,886
UP	96,744	1.321158	127,814
DOWN	66,999	1.851191	124,028
SAME	36,137	2.741854	99,082
TOTAL	241,731		456,810

Table 3: Information Required for Predicting Six Outcome Model

	# of Indiv	bits per indiv	Info
MISS	41,851	2.530068	105,886
UP, <= $1000	30,826	2.971183	91,590
UP, > $1000	65,918	1.874658	123,574
DOWN, >= -$1000	29,784	3.020793	89,971
DOWN, < -$1000	37,215	2.699446	100,460
SAME	36,137	2.741854	99,082
TOTAL	241,731		610,563

Using a set of 25 variables derived from CSE, ESD, and OFM data and a preliminary neural network simulation, we have obtained a preliminary measure of predictability over the seven outcome quarters for models with two outcome categories, four outcome categories, and six outcome categories.

Figure 1 shows that regardless of the model, the input information becomes less useful for prediction as we attempt to predict further into the future. But even with this preliminary approach 64% of the information required for prediction of two outcomes in the seventh evaluation quarter can be extracted from input variables. As we try to gain more definition in prediction, by creating more categories, the quality of prediction also decays. For four categories, we can extract only about 50% of the required information in the seventh quarter, and for six categories only about 43 percent.

Figure 2 shows that the prediction quality can vary for the separate outcomes within a model. In early quarters for the 4 outcome model we might have more confidence in predictions for "SAME" and "UP," where in later quarters we might have more confidence in predictions for "UP" and "DOWN." Predictions for "MISS" appear to always be the least certain.

Figure 1: Percent of Total Information Extracted in Neural Network Modeling

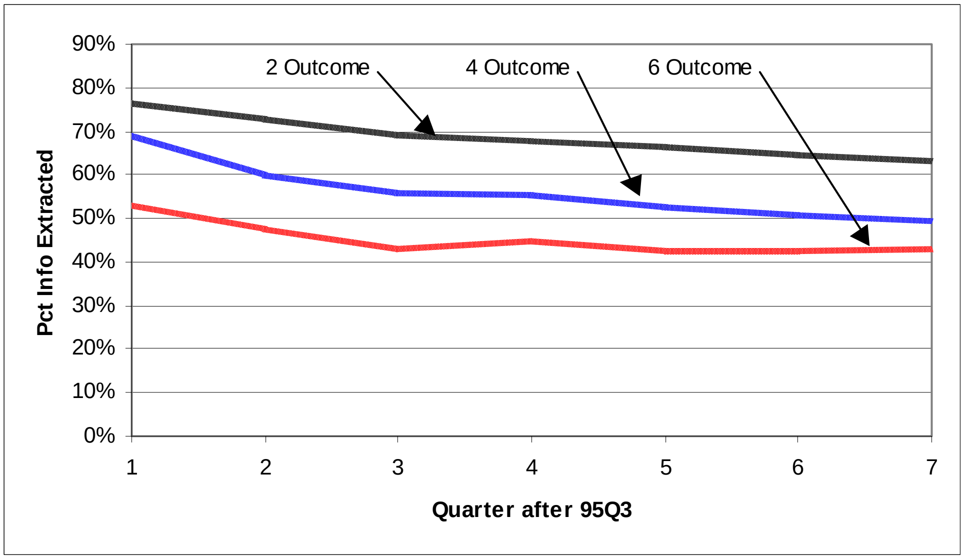
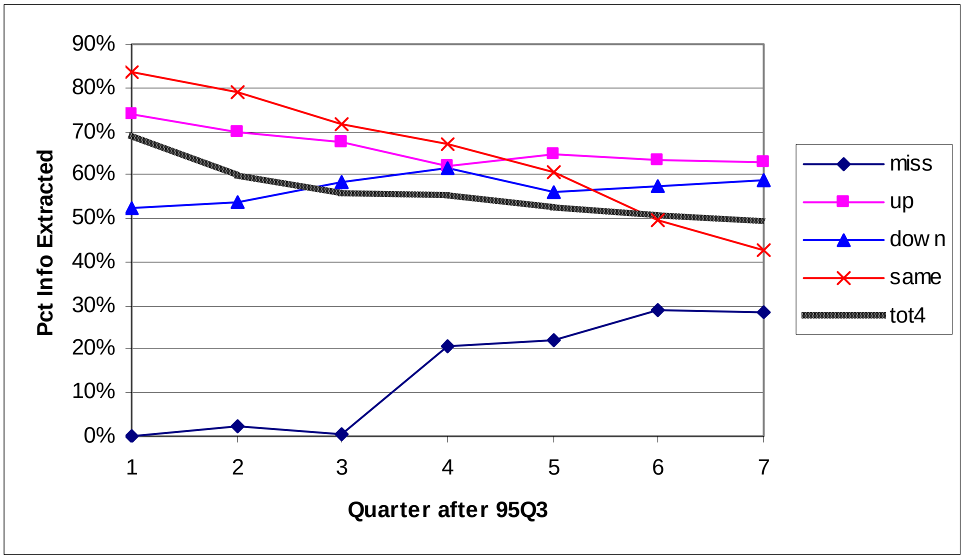


Figure 2: Percent of Information Extracted for Each Category in Neural Network Modeling



Progress with NADB Cross-Match Data

In June 2000 we obtained individual level data from the cross-match for use of services from Division of Alcohol and Substance Abuse (DASA), Division of Vocational Rehabilitation (DVR), Economic Services Administration (ESA), Medical Assistance Administration (MAA), and Mental Health Division (MHD).

After considerable work with the NADB cross-match data we have decided, for the present, to not include this data in our predictive model. While some variables derived from NADB data do significantly boost predictability, the boost is quite small and does not appear to justify the downside of using NADB data:

1) There is a possible bias because not all of the 241,731 NCP were in the NADB submittal - 46,330 NCPs were missed, about 19% of the cohort. Outcomes for the 46,330 NCPs not in the submittal are quite different from the outcomes for the 195,401 NCPs who were in the submittal.

2) The model would be less transportable to other time frames with NADB input since we do not have comparable information in other periods.

3) A more complex model results with the NADB variables, and would be much harder to optimize.

We describe our work with the NADB data here. We believe this approach is potentially useful because there clearly are relationships between public service use and outcomes. But the time frame of the data is wrong – it gives us only public service use in State Fiscal Year 1994 – and low usage of public services by NCPs limit the utility of NADB data in predicting individual outcomes.

The NADB data is quite complex, and we have sought ways to summarize the detailed nature of the data so that the information could be captured in a reasonable number of variables. We can consider the NADB information at several levels:

1) At the overall level we have information on the total number of DSHS services (all divisions) used by the NCP. This information can be used as a numerical variable, or simply to indicate those who used any DSHS service.

2) At the DSHS divisional level we have the divisional program use for 5 divisions, and through difference with overall use, the sum of program use in all other divisions. Again, this information can be used numerically or as an indicator.

3) At the program level we have information on the use of 159 separate services. This only indicates use or no use of the service. This is too much detail to include in a predictive model for arrearage debt, so we have considered several possible ways to aggregate this information.

Overall

Table 4 shows a summary of use of DSHS services for the 95Q3 arrearage cohort. Because of timing issues we did not obtain NADB information on the entire cohort of 241,731 NCPs. Table 4 shows that only about 25% of NCPs submitted for cross-match showed any use of DSHS services, and that heaviest usage occurred in ESA and MAA services.

Table 4: Cross-Match with DSHS Service Records

	Non-Custodial Parent Arrears Cohort	
	N	%
Submitted	195,401	100.0%
No Pgms	146,755	75.1%
Any Pgm	48,646	24.9%
Pgm in 5 Div	46,869	24.0%
DASA	9,055	4.6%
DVR	2,631	1.3%
ESA	41,969	21.5%
MAA	32,799	16.8%
MHD	3,905	2.0%
Other Div Pgms	26,836	13.7%

See Table 7 for Services and Programs within the five Divisions

Division

Within the 5 divisions for which we have individual level data, most of the NCPs who used any service used services from multiple divisions. There were only 14,185 NCPs who used services from a single division. Table 5 shows the patterns of divisional use, and 7th quarter arrearage outcomes for the NCPs with each pattern. There appear to be relationships between patterns of service use and arrearage outcomes. For example, considering only patterns with more than 500 individuals, the percentage with increasing arrears varies from 38% to 58%.

Table 5: Patterns of Divisional Service Use and Outcomes

Any Program Use In					*Arrears Outcomes*				Number
DASA	**DVR**	**ESA**	**MAA**	**MHD**	**miss**	**Up**	**down**	**same**	**With pattern**
0	0	0	0	0	15%	38%	31%	16%	148532
0	0	1	1	0	17%	46%	26%	11%	21874
0	0	1	0	0	12%	51%	30%	7%	9888
1	0	1	1	0	12%	55%	23%	10%	4703
0	0	1	1	1	23%	43%	23%	11%	1938
1	0	0	0	0	10%	52%	31%	7%	1786
0	0	0	1	0	18%	44%	29%	9%	1384
0	1	1	1	0	16%	38%	36%	10%	836
1	0	1	1	1	15%	53%	22%	10%	785
1	0	1	0	0	7%	58%	28%	8%	746
0	1	0	0	0	14%	39%	36%	11%	653
0	0	0	0	1	13%	48%	28%	10%	474
1	1	1	1	0	13%	48%	31%	8%	426
1	0	0	1	0	12%	60%	23%	5%	320
0	1	1	0	0	14%	46%	31%	9%	238
0	1	1	1	1	16%	38%	31%	15%	229
0	0	1	0	1	14%	44%	33%	9%	141
1	1	1	1	1	20%	39%	31%	10%	115
0	0	0	1	1	17%	36%	35%	11%	110
1	1	0	0	0	5%	63%	25%	8%	40
1	0	0	0	1	10%	51%	36%	3%	39
1	0	0	1	1	12%	61%	21%	6%	33
0	1	0	1	0	14%	28%	52%	7%	29
1	1	1	0	0	4%	46%	50%	0%	28
1	0	1	0	1	0%	65%	29%	6%	17
1	1	0	1	0	15%	38%	38%	8%	13
0	1	0	0	1	8%	58%	33%	0%	12
0	1	1	0	1	75%	25%	0%	0%	4
0	1	0	1	1	25%	25%	50%	0%	4
1	1	0	0	1	0%	33%	0%	67%	3
1	1	1	0	1	100%	0%	0%	0%	1

Using a logistic regression to sort out these patterns, Table 6 gives results controlled for use of other division's programs. An odds ratio greater than 1 tells us that the particular outcome is more likely if the service is used, and an odds ratio less than 1 tells us that the outcome is less likely if the service is used. For example, NCPs who used DVR services are more likely to have decreasing arrearage debt and less likely to have increasing arrearage debt.

Table 6: Effects of Divisional Service Use – Odds Ratios
Only Significant Effects Shown

ODDS RATIOS

	DASA	DVR	ESA	MAA	MHD
MISS	0.65		0.80	1.45	1.31
UP	1.54	0.81	1.59	0.88	
DOWN	0.90	1.42	0.91	0.85	0.91
SAME	0.70	0.83	0.54	1.22	

Program

The 159 separate programs are listed in Table 7 with the number of NCPs using each service. The patterns of service use at the program level are quite complex and will not be presented. There are two methods of aggregation which were carried forward into the neural network simulation.

The first method groups programs together in terms of similarity of function, as suggested in discussions with staff from each of the divisions. We call these functional patterns, abbreviated as Fpatt_1 through Fpatt_30. Table 8 shows this grouping.

The second grouping method used logistic analysis to estimate each program's effect on arrearage outcomes, controlled for all other program use. The programs are then grouped according to their effect on outcomes, which we call outcome patterns, abbreviated as Opatt_1 through Opatt_48. Since there are three possible effects – use of the service makes the outcome more likely, makes it less likely, or has no effect – and four possible outcomes, there are mathematically 81 possible patterns. Two of these are not possible in actuality because not all outcomes can increase in likelihood, nor can all outcomes decrease in likelihood. Thus 48 out of 79 possible outcome patterns are seen. Table 9 shows 25 of these patterns, listed in descending order of use.

Table 7: Program Identification

Pgm#	Division	Program/Service	# of clients
1	DASA	ADATSA Assessments	3,292
2	DASA	ADATSA Assessment-Lab Fees	151
3	DASA	ADATSA Psychological Examination	23
4	DASA	ADATSA CPI and Stipend	1,731
5	DASA	Opiate Substitution Tx- Non-T19	140
6	DASA	Opiate Substitution Tx-T19	264
7	DASA	Outpatient Assessment-Reg T19	1,238
8	DASA	Outpatient Assessment-Preg/Parent-T19	342
9	DASA	Outpatient Assessment-EPSDT-T19	2
10	DASA	Outpatient Intake-Reg T19	702
11	DASA	Outpatient Intake-Preg/Parent T19	191
12	DASA	Outpatient Intake-EPSDT-T19	2
13	DASA	Outpatient Physical-Reg T19	82
14	DASA	Outpatient Physical-Preg/Parent T19	1
15	DASA	Outpatient Individ/Group Therapy-RegT19	1,769
16	DASA	Outpt Individ/Grp Therapy-Preg/Parnt T19	367
17	DASA	Outpt Individ/Grp Therapy-EPSDT-T19	7
18	DASA	Alcohol Detoxification-Title 19	32
19	DASA	Drug Detoxification-Title 19	16
20	DASA	Drug Detoxification-Non T19	700
21	DASA	Alcohol Detoxification-Non Title 19	807
22	DASA	Outpatient Tx-Preg/Post Non-T19	66
23	DASA	Outpatient Tx-Other Non-T19	2,085
24	DASA	ADATSA Outpatient Treatment	1,172
25	DASA	Outpatient Assessment-Reg Non-T19	813
26	DASA	Outpatient Assmnt-Preg/Post Non-T19	118
27	DASA	ADATSA Intensive Inpatient Treatment	1,477
28	DASA	ADATSA Recovery House	475
29	DASA	ADATSA Extended Care Recovery House	312
30	DASA	ADATSA Dual/Diff Diag Resid Tx	72
31	DASA	ADATSA Long Term Residential Tx	153
32	DASA	DASA Residential-Preg/Parent Non-T19	130
33	DASA	DASA Residential-Preg/Parent T19	30
34	DASA	DASA Residential-Youth	19
35	DASA	DASA Urinalysis (MMIS)	27
36	DASA	DUI/Def Pros Assessments	674
37	DASA	Transitional Housing	65
38	DASA	Pioneer North MICA-DASA	10
39	DASA	Pioneer North ICDT-DASA	32
40	DASA	Pioneer North ICDT-DASA-pre 1/1/94	29
41	ESA	Aged, Blind, and Disabled	61
42	ESA	Presumptive Disability	1,833

43	ESA	SSI-State Share	3,119
44	ESA	GA-Unemployable Grants (WR)	3,834
45	ESA	GA-H Needy Child with Guardian	3
46	ESA	ADATSA Protective Payee	611
47	ESA	SSI Facilitation Program	1,622
48	ESA	DIA Protective Payee Fee	107
49	ESA	Refugee Grants	8
50	ESA	AFDC Regular	13,545
51	ESA	AFDC Employable	8,527
52	ESA	GA-S Pregnancy Grants	584
53	ESA	Food Stamp Benefits	40,048
54	ESA	FSA Transitional Child Care	8
55	ESA	AFDC/JOBS Child Care Employed	38
56	ESA	AFDC/JOBS Child Care Regular	63
57	ESA	AFDC/JOBS Child Care Transitional	25
58	ESA	AFDC/GAU Eligibility Determination	4,108
59	ESA	JOBS Case Management-ES	36
60	ESA	JOBS Assessment-ES	469
61	ESA	JOBS Education-ES	783
62	ESA	JOBS Job Skills Training-ES	281
63	ESA	JOBS Volunteer Work-ES	30
64	ESA	JOBS On-the-Job Training-ES	24
65	ESA	JOBS One Time Work Expense-ES	252
66	ESA	JOBS Job Search-ES	423
67	ESA	JOBS Job Placement-ES	0
68	ESA	JOBS Staff Direct Service-ES	3,591
69	ESA	JOBS Case Management-DSHS	173
70	ESA	JOBS Assessment-DSHS	310
71	ESA	JOBS Education-DSHS	201
72	ESA	JOBS Job Skills Training-DSHS	18
73	ESA	JOBS Volunteer Work-DSHS	1
74	ESA	JOBS On-the-Job-Training-DSHS	1
75	ESA	JOBS Job Search-DSHS	178
76	ESA	JOBS Job Placement-DSHS	3
77	ESA	JOBS Staff Direct Service-DSHS	1,081
78	MAA	ER-Other Hospital Inpatient	1,346
79	MAA	Other Inpatient Hospital	2,347
80	MAA	ER-Hospital Outpatient Other	11,076
81	MAA	Psychiatric-Outpatient Hospital	5
82	MAA	Other Outpatient Hospital	8,198
83	MAA	ER-Physician	10,840
84	MAA	ER-Psychiatry-Physician	25
85	MAA	ER-Other Physician Services	2,693
86	MAA	Psychiatry-Physician	1,268
87	MAA	Other Physician Services	19,638
88	MAA	Prescription Drugs	21,454

89	MAA	Dental Services	7,964
90	MAA	Hospice Care	1
91	MAA	Other Medical	13,904
92	MAA	Indian Health Care Center	561
93	MAA	Rural Health Care Center	371
94	MAA	Durable Medical Equipment (DME)	1,296
95	MAA	Home Health Services	153
96	MAA	EPSDT	721
97	MAA	Psychologist	92
98	MAA	Managed Care Payments	10,510
99	MAA	Medicare Part A Premiums	1
100	MAA	Medicare Part B Premiums	855
101	MAA	Maternity Case Management	1,057
102	MAA	Medical Eligible With Medical Service	27,454
103	MAA	Medical Eligible No Medical Service	4,131
104	ESA	Refugee CSO Case Management	447
105	ESA	English as a Second Language Training	18
106	ESA	Employment Services	161
107	ESA	Refugee Unaccompanied Minors	0
108	DVR	Supported Employment Case Management	35
109	DVR	Regular Case Management	2,597
110	DVR	Medical or Psychological Svc-SE Clients	5
111	DVR	Medical or Psychological Sv-NonSE Client	791
112	DVR	Vocational Assessment & Work Skill-SE	4
113	DVR	Voc Assmnt & Work Skill-NonSE Clients	151
114	DVR	Personal Support Services-SE Clients	3
115	DVR	Personal Support Services-Non SE Clnts	651
116	DVR	Training, Education, and Supplies-SE	12
117	DVR	Training, Education, Supplies-Non SE	589
118	DVR	Placement Support-SE Clients	11
119	DVR	Placement Support-Non SE Clients	543
120	DVR	Transportation-SE Client	0
121	DVR	Transportation-Non SE Client	168
122	DVR	Long-Term SE Followup	1
123	DVR	DVR Other Service-SE Clients	0
124	DVR	DVR Other Services-Non SE Clients	21
125	MHD	MHD Adult Day Treatment	291
126	MHD	MHD Child Day Treatment	17
127	MHD	Crisis Services	1,831
128	MHD	MHD Stabilization Services	51
129	MHD	Adult Acute Diversion	18
130	MHD	Child/Adolescent Acute Diversion	0
131	MHD	MHD Outpatient Treatment Group	521
132	MHD	MHD Outpatient Treatment Family	90
133	MHD	MH Individual Tx Services-in Facility	1,882
134	MHD	MH Individual Tx Svcs-Out of Facility	877

135	MHD	Other CMH Provider Services	225
136	MHD	Intake in Community Mental Health Prov	1,128
137	MHD	Psychological Assessment in CMH Provider	121
138	MHD	Special Population Evaluation	25
139	MHD	Interdisciplinary Evaluation	5
140	MHD	Individual Medication Management	998
141	MHD	Group Medication Management	37
142	MHD	Program for Adaptive Living Skills(PALS)	6
143	MHD	Prg Offer'g Rehab,Trng,Adlt Liv PORTAL	3
144	MHD	Child Study & Treatment Center (CSTC)	1
145	MHD	East St Hosp-Adlt Psychiatric Extended	2
146	MHD	East St Hosp-Adlt Psychiatric Acute	49
147	MHD	East St Hosp-Geriatric Psychiatric	3
148	MHD	East St Hosp-Mentally Ill Offenders	32
149	MHD	East St Hosp-Special Care Medical	2
150	MHD	West St Hosp-Adlt Psychiatric Extended	22
151	MHD	West St Hosp-Adlt Psychiatric Acute	85
152	MHD	West St Hosp-Geriatric Psychiatric	3
153	MHD	West St Hosp-Mentally Ill Offenders	62
154	MHD	West St Hosp-Special Care Medical	4
155	MHD	Involuntary Commitments-Community Hosptl	265
156	MHD	RSN – Evaluation & Treatment Centers	93
157	MHD	Community Psychiatric Inpatient	692
158	MHD	Pioneer North MICA-MHD	10
159	MHD	Pioneer North ICDT-MHD	32

Table 8: Program Functional Group Patterns

FG#	Svc	Division	# of clients with pattern
1	Assessm	DASA	2,513
2	OP		5,466
3	Opiate		404
4	resid tx		2,739
5	Other		3,475
6	Detox		1,555
7	Adassessm		3,466
8	Disability	ESA	10,469
9	AFDC R		13,545
10	AFDC E		8,527
11	FS		40,048
12	child care		134
13	Assessment		5,096
14	JOBS		6,867
15	Payee		1,302
16	Other		637
17	IP	MAA	3,693
18	OP		19,279
19	PHYS		34,464
20	DRUG		21,454
21	DENTAL		7,964
22	OTHER		61,107
23	DVR	DVR	5,582
24	DAY TX	MHD	308
25	OP		3,370
26	CRISIS		1,900
27	ASSMT		2,407
28	N		1,128
29	MIO		94
30	OTHER		267

Table 9: Program Outcome Patterns

Partial Listing

1=outcome more likely; -1=outcome less likely; 0=no effect

OG#	Miss	up	Down	same	# clients with pattern	# Pgms in pattern
1	0	0	0	0	64,161	95
2	0	0	0	1	41,442	7
3	1	0	0	0	20,445	7
4	0	-1	0	0	19,251	5
5	0	-1	1	0	13,545	4
6	1	-1	1	0	13,130	4
7	-1	1	-1	0	12,453	3
8	0	0	-1	0	11,833	3
9	0	1	-1	0	10,388	3
10	1	-1	-1	1	8,207	3
11	-1	1	0	0	7,046	2
12	0	-1	0	1	5,041	2
13	0	0	0	-1	3,741	2
14	0	0	1	0	3,656	2
15	0	1	-1	-1	2,936	2
16	0	1	0	-1	2,829	2
17	0	1	0	0	2,693	2
18	1	-1	0	0	2,391	2
19	1	-1	0	1	2,244	2
20	1	0	-1	1	2,206	2
21	-1	0	0	0	2,159	1
22	-1	0	1	-1	2,007	1
23	-1	1	0	-1	1,882	1
24	0	0	-1	1	1,638	1
25	1	1	-1	0	1,546	1

While there are clearly relationships between use of DSHS services and child support arrearage outcomes, none of the NADB variables are, by themselves, useful in prediction of individual outcomes. But as discussed in the next section, a group of 8 NADB variables (see Table 10) show small but significant predictive power in combination with other variables. When NADB variables were included in modeling, only NCPs submitted for matching (N=195,401) were included in the modeling procedure, with a different random sample of 5000 NCPs used for neural network training.

Table 10: NADB Variables with Predictive Power

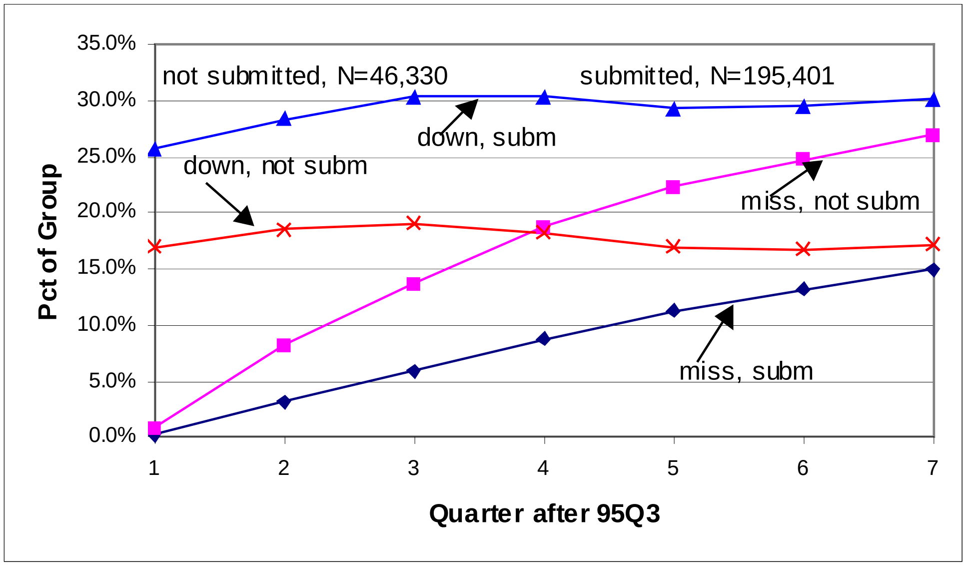
Opat_42	Pgm 30
Fpat_18	Pgm 80, Pgm 81, & Pgm 82
Opat_38	Pgm 31
mhdpgms	# of programs from MHD Division
Opat_17	Pgm 85
Opat_30	Pgm 140
Opat_35	Pgm 74, Pgm 92, & Pgm 122
Opat_44	Pgm 55

See Table 7 for Programs

Possible Bias in the NADB Sample

Because of timing issues 46,330 NCPs from the 95Q3 cohort were not submitted for matching with NADB data. These NCPs were not in DCS records for FY94. However, as seen in Figure 3, outcomes for these 46,330 NCPs were greatly different from outcomes for the 195,401 cohort NCPs who were submitted for match. While the two groups are not very different in the percentage with increasing arrears, or arrears which do not change, they are very different in the percentage with decreasing arrears and the percentage with missing information. Relative to the 195,401 who were submitted in the NADB match, the 46,330 not submitted appear to be much more likely to be missing from the quarterly records, and much less likely to have decreasing arrears.

Figure 3: Comparing Outcomes for NCPs Submitted, or Not Submitted, for NADB Matching



Preliminary Selection of Variables and Net Optimization

Without any information in the four outcome category model, other than the knowledge that UP is the most likely outcome, the best prediction strategy would be to predict all individuals arrearage outcomes as UP. This is in fact what logistic or neural network predictions tend to do, when the input vectors contain no information. This will give correct answers for 96,744 individuals, about 40% of the cohort. This is an example why simply using the number of correct predictions as a criteria is not adequate. The approach of information theory gives a better quantitative measure of the quality of a prediction. With no input information, this gives us the information content value – 127,814 bits - of the knowledge that UP is the most likely outcome (see Table 2). This is also approximately the information content in the outcome sample used in building either a logistic or a neural network prediction. Any prediction which shows an information content greater than 127,814 bits contains information in the input vectors, and this allows us to estimate the amount of information present in any input, and also forms a basis to evaluate different prediction models.

We first selected 110 variables to test as possible input vectors for a predictive model. Our approach anticipated selection of a small subset (perhaps 10 - 20 variables) which appears to contain the vectors with the highest information content for arrearage prediction. Then using this subset, to optimize the neural network used in prediction. Neural network modeling has great flexibility, and this allows us to alter many features in trying to obtain the best predictions – that is, to obtain the most efficient extraction of the information present in the input.

We tested input variable information by comparing the prediction information content to that for the same variable submitted in scrambled order. Since a prediction may be sensitive to the values and distribution of an input this allows for a completely fair comparison.

The 110 variables were first tested individually in neural network simulations predicting outcomes in the seventh quarter after 95Q3. Only 10 of these variables (none derived from NADB data) had consistent predictive power by themselves. Testing these 10 variables as a group, we found that only 8 variables were needed. Testing the remaining 100 variables, each added in turn as the ninth variable, showed that 8 more variables, all derived from NADB data, had predictive power in the group. Finally testing the group of 16 variables we showed a significant, but small, boost in predictive power by including the 8 NADB variables. However, as discussed in the previous section, we have decided against inclusion of NADB data. We thus plan on optimizing our neural network model using eight variables. Seven of these are derived from CSE data, and one is derived from ESD data.